SVD Based Features for Image Retrieval

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***Abstract*-In this paper we present a new method for Content Based Image Retrieval (CBIR). Image signature computed by using the Singular Value Decomposition (SVD). Singular values used as a feature are obtained from SVD of full image and sub block of image with different color spaces. Seven color spaces are used for the proposed method. Singular values for the feature vectors are 8,16,32,64 and 200 for the full image and it is different for block based SVD. For block based SVD image we use 8x8, 16x16, 32x32, 64x64 and 128x128 sub blocks to calculate feature vector. So we can compare the result of different color with full and block based SVD. Similarity between the query image and database image measured here by using simple Euclidean distance (ED) and Bray Curtis distance (BCD). The average precision and average recall of each image category and overall average precision and overall average recall is considered for the performance measure. Proposed method tested on the database include 1200 images has 15 different classes to compare the performance.**

Keywords*-*CBIR; SVD; RGB; YCbCr; YUV; CXY; R'G'I; HSV; Precision; Recall; Euclidean Distance; Bray Curtis Distance

I. INTRODUCTION

In recent years, there has been significant effort put into understanding the real world implications, applications, and constraints of the technology. We try to understand image retrieval in the real world and discuss user expectations, system constraints and requirements. Designing a real-world image search engine capable of serving all categories of users requires understanding and characterizing user-system interaction and image search, from both user and system points-of-view. The process of digitization does not in itself make image collections easier to manage. Some form of cataloguing and indexing is still necessary – the only difference being that much of the required information can now potentially be derived automatically from the images themselves.

An image which is represented simply as a collection of gray or colored pixel values in the digital form does not carry the semantic information associated with the image. However when talking about similarity, we might refer to its similarity in appearance or in semantics. For example for us a picture of a tiger on snow or grass is similar although its color information may be quite different. Also an image of the same person young and old would be similar to us as we are the semantic knowledge of it being associated to the person is there with us. It is difficult and sometimes even impossible in absence of additional information to infer semantic deductions from the set of pixels. Every CBIR system is completely described by answering the two questions: (a) how to mathematically describe an image (computing the feature vector or image signature); and (b) how to assess the similarity (similarity metric).

The typical CBIR system performs two major tasks. The first one is feature extraction (FE), where a set of features, called feature vector, is generated to accurately represent the content of each image in the database. The second task is similarity measurement (SM), where a distance between the query image and each image in the database using their feature vectors is used to retrieve the top "closest" images. For feature extraction in CBIR there are mainly two approaches: feature extraction in spatial domain and feature extraction in transform domain.

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. "Content-based" means that the search will analyse the actual contents of the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. Without the ability to examine image content, searches must rely on metadata such as captions or keywords, which may be laborious or expensive to produce. The need to find a desired image from a collection is shared by many professional groups, including journalists, design engineers and art historians.

Users needing to retrieve images from a collection come from a variety of domains, including crime prevention, medicine, architecture, fashion and publishing. Remarkably little has yet been published on the way such users search for and use images, though attempts are being made to categorize users' behaviour in the hope that this will enable their needs to be better met in the future.

The term CBIR [10-25] seems to have originated in 1992, when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features. The techniques, tools and algorithms that are used originate from fields such as statistics, pattern recognition, signal processing, and computer vision. Historians from a variety of disciplines – art, sociology, medicine, etc. – use visual information sources to support their research activities. Archaeologists also rely heavily on images.

Current indexing practice for images relies largely on text descriptors or classification codes, supported in some cases by text retrieval packages designed or adapted specially to handle images. Again, remarkably little evidence on the effectiveness of such systems has been published. User satisfaction with such systems appears to vary considerably. Text based image retrieval required manual annotation for every image. Describing every image by using the text string is very time consuming task. Text string describes the content of image that dependent on the user.

To make feature vector effective and smaller Wavelet Transform, DCT and Walsh Transform applied on the row

mean and column mean [1, 2, 3] and row and column pixel distribution of BMP image. We can make a feature vector by taking moments of wavelet coefficients [4]. Color histograms bins [5] and histogram bins moments [6] also make feature vector effective. Bit plane pixel distributions, bit plane slicing [7, 8] used for computing feature vector for image.

In the second task take a query image compute the feature vector and find out the Euclidean distance (similarity). The images whose minimum Euclidean distance can be retrieved [3, 13, 14, 15].

II. SINGULAR VALUE DECOMPOSITION (SVD)

The Singular Value Decomposition (SVD) for square matrix was discovered independently by Beltrami in 1873 and Jordan in 1874 and extended to rectangular matrix by Eckart and Young in 1930.

The singular value decomposition of a rectangular matrix A is decomposed in the form

$$A = UDV^T \tag{1}$$

Where A is an $m \times n$ matrix.

U, V are the orthogonal matrices.

D is a diagonal matrix comprised of singular value of A.

The singular values $\sigma_1 \geq \sigma_2, \ldots\ldots\ldots\ldots\ldots \geq \sigma_n \geq 0.$ appears in the descending order along with the main diagonal of D. The singular values are obtained by taking the square root of Eigen value of AA^T and $A^T A$.

Above Equation (1) can be written as

$$A = UDV^T \tag{2}$$

$$A = [u_1, u_2, \ldots\ldots u_n] \begin{bmatrix} \sigma_1 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 \\ 0 & 0 & .. & 0 \\ 0 & 0 & 0 & \sigma_n \end{bmatrix} \begin{bmatrix} v_1^T \\ | \\ | \\ v_n^T \end{bmatrix} \tag{3}$$

The relation between SVD and Eigen values are given below

$$A = UDV^T$$

Now

$$AA^T = UDV^T (UDV^T)^T = UDV^T VDU^T = UD^2 U^T \tag{4}$$

Also

$$A^T A = (UDV^T)^T UDV^T = VDU^T UDV^T = VD^2 V^T \tag{5}$$

Thus U and V are calculated as a Eigen vector of AA^T and $A^T A$ respectively. The square root of Eigen values are the singular values along the diagonal of matrix D. If the matrix A is real then the singular values are always real number and U and V are also real.

Properties of SVD are

- The singular values $\sigma_1, \sigma_2, \ldots\ldots\ldots\ldots\ldots\sigma_n$ are unique; however the matrix U and V are not unique.
- The matrix U can be computed through the Eigen vector of $A^T A$.
- The rank of matrix A is equal to the number of its non-zero singular value.

Application of SVD in image processing is

- SVD approach can be used in the image compression.
- SVD can be used n the face recognition.
- SVD can be used in the texture classification

III. COLOR PLANE CONSIDER FOR THE PROPOSED METHOD

As like Gray scale and RGB color planes SVD and block based SVD applied on the other color planes for computing the feature vector and compare the performance.

A. YCbCr Color Plane

We applied SVD on YCbCr color planes. Conversion of RGB to YCbCr is given using Equation (6).

$$\begin{vmatrix} Y \\ Cb \\ Cr \end{vmatrix} = \begin{vmatrix} 0.2989 & 0.5866 & 0.1145 \\ -0.1688 & -0.3312 & 0.5000 \\ 0.5000 & -0.4184 & -0.0816 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix} \tag{6}$$

B. YUV Color Plane

In YUV color space Y represent the luminance and U, V represent the chrominance information of given color image. Color conversion of RGB to YUV is given by Equation (7)

$$\begin{vmatrix} Y \\ U \\ V \end{vmatrix} = \begin{vmatrix} 0.299 & 0.587 & 0.144 \\ -0.14713 & -0.22472 & 0.436 \\ 0.615 & -0.51498 & 0.10001 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix} \tag{7}$$

C. HSV Color Plane

H (Hue), S (Saturation) and V (Value) is considered as Tint, Shade and Tone by artists. Value represents the intensity of color. The Hue and Saturation components are intimately related to the way human eye perceives colour resulting in image processing algorithms with physiological basis. Conversion formula from RGB to HSV is given in the Equations (8), (9), and (10).

$$H = \cos^{-1}\left[\frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\sqrt{\left[(R-G)^2+(R-B)(G-B)\right]}}\right] \tag{8}$$

$$S = 1 - \frac{3}{R+G+B}\left[\min(R,G,B)\right] \tag{9}$$

$$V = \frac{1}{3}(R+G+B) \tag{10}$$

D. R'G'I Color Plane [32]

Here we have to used R'G'I color model. This model can be used to separate low and high frequencies in the image without losing any information from the image. This, in turn, allows both distinguishing possible ROIs and retrieving their proper color for further ROI analysis. To get R'G'I components we need the conversion of RGB to R'G'I components. The RGB to R'G'I conversion matrix given in Equations 11, 12, and 13 gives the R',G',I components of image for respective R, G, B components.

$$R' = \frac{R.256}{(R+G+B)} \quad (11), \qquad G' = \frac{G.256}{(R+G+B)} \quad (12)$$

$$I = \frac{(R+G+B)}{3} \tag{13}$$

E. CXY Color Plane

Conversion of RGB to CXY color plane is given in the Equation (14).

$$\begin{vmatrix} C \\ X \\ Y \end{vmatrix} = \begin{vmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.14 \\ 0.000 & 0.006 & 1.116 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix} \tag{14}$$

IV. FEATURE EXTRACTION

A. SVD of Full Image

When SVD of image having size NXN is computed then we get singular values [13, 37, 36]. These singular values appear in decreasing order. Feature vector size is different because of when we take one, eight, sixteen, thirty two and sixty four singular values for the image reconstruction then the appearance of the image is shown in Fig. 1. So in this paper the feature vector size is 8,16,32,64 and 200 for gray scale image and 24,48,93,192 and 600 for color image to find out which SVD values feature suitable for CBIR. Recommended font sizes are shown in Table Ⅰ.

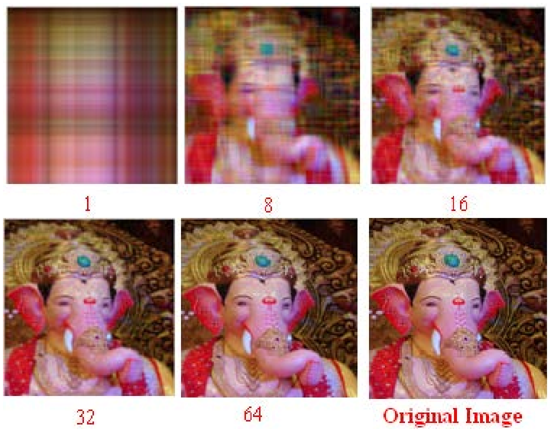

Fig. 1 Reconstruction of the images for different value of SVD

From Fig. 1 it is clear that as the SVD values goes on increasing the visual quality of the reconstructed image approaches the original image.

TABLE Ⅰ IMAGE CATEGORIES AND NUMBER OF IMAGES

Sr. No.	Name of Category	No. of Images
1	Motorbikes	100
2	Beaches	100
3	Historical Mountains	100
4	Buses	100
5	Dinosaurs	100
6	Elephants	100
7	Flowers	100
8	Horses	100
9	Tribal Peoples	68
10	Mountains	62
11	Flying Birds	63
12	Flower lawn	48
13	sunset	48
14	Butterfly Scenery	52
15	Guitar	59

B. Block Base SVD

In Section IV-A feature vectors having truncated singular values of image. We are testing what is the effect of SVD coefficients on the retrieval accuracy when it goes on increasing. Without truncation when image is divided into sub block and then SVD of each block is computed. In this method the feature vector size is goes on increasing as the image block size decreasing. In this paper we use 8X8, 16X16, 32X32, 64X64 and 128X128 block size of image.

V. EXPERIMENTAL PESULT

A. Feature Vector Matching

When a query image is submitted by a user, we need to compute the feature vector as before and match it to the precomputed feature vector in the database. This is shown in Fig. 2 of block diagram of retrieval process consists of feature extraction process, feature vector storage process and similarity measure process. The feature extraction process is based upon the following. Which the batch feature extraction and storage process as described in the following steps.

a. Images taken one by one from the database.
b. Feature is computed using the feature extraction process.
c. Make feature vector database for given database images.

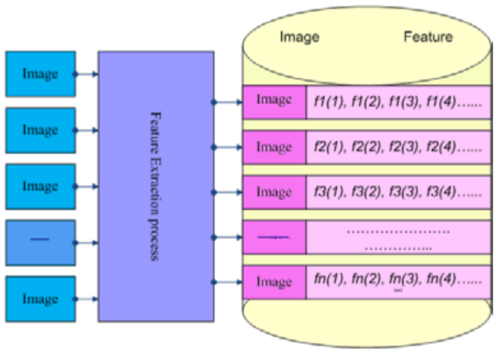

Fig. 2 Feature extraction and storage process for an image collection

After that query image and database image matching is done using similarity measures. In this paper two similarity measures are used Euclidean Distance (ED) and Bray Curtis Distance (BCD) for the comparison. Minkowski (Euclidean distance when r=2) distance is computed between each database image & query image on feature vector to find set of images falling in the class of query image.

$$Ed(Q,I) = \left(\sum_{M=0}^{M-1} \left| H_Q - H_I \right|^r \right)^{1/r} \tag{15}$$

Where Q-Query image
I- Database image
H_Q-Feature vector query image.
H_I-Feature vector for database image
M-Total no of component in feature vector

Bray Curtis Distance is computed between query image and database image using Equation 16

$$Bd(Q,I) = \frac{\sum_{k=1}^{n} \left| H_{Qk} - H_{Ik} \right|}{\sum_{k=1}^{n} (H_{Qk} - H_{Ik})} \tag{16}$$

Where n-Total no of component in feature vector.

Q-Query image

I-Database image

HQk-Feature vector query image

HIk-Feature vector for database image

B. Performance of CBIR

Performance of image retrieval system can be analysed by using two parameters precision and recall. As shown in Fig. 3. Testing the effectiveness of the image search engine is about testing how well can the search engine retrieve similar images to the query image and how well the system prevents the return results that are not relevant to the source at all in the user point of view. A sample query image must be selected from one of the image category in the database. When the search engine is run and the result images are returned, the user needs to count how many images are returned and how many of the returned images are similar to the query image. The first measure is called Recall. All the relevant images from the database are recall. The equation for calculating recall is given below:

$$\text{Recall} = \frac{\text{Number\_of\_relevant\_images\_retrived(A)}}{\text{Total\_number\_of\_relevant\_images\_in\_database(A+D)}} \quad (17)$$

The second measure is called Precision. It is accuracy of a retrieval system to present relevant as well as non-relevant images from the database which is mathematically given as:

$$\text{Precision} = \frac{\text{Number\_of\_relevant\_images\_retrived(A)}}{\text{Total\_number\_of\_images\_retrived(A+B)}} \quad (18)$$

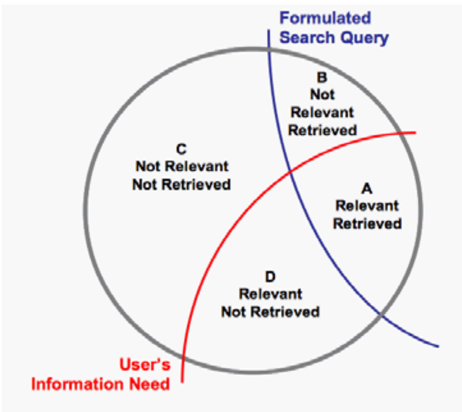

Fig. 3 Evaluation of CBIR

C. Implementation and Result

The implementation of CBIR technique is done in MATLAB 7.0 using a computer with Intel Core 2 Duo Processor T8100 (2.1GHz) and 2 GB RAM. We have tested performance with a general purpose image database that consist of 1200 with 15 categories some from Corel Image Gallery. Some sample images from of general database by randomly selecting one image from each category is shown in Fig. 4. Categories and total no of images are given below.

The average precision is calculating by using following Equations 19, 20. The average precision for images belonging to the qth category (A_q) has been computed by:

$$\bar{P}_q = \sum_{k \in Aq} P(I_K) / \left|(A_q)\right|, q = 1,2,....5 \quad (19)$$

Where $P(I_k)$ is the precision for query image I_k .

Finally, the average precision is given by:

$$\bar{P} = \sum_{q=1}^{5} \bar{P}_q / 5 \quad (20)$$

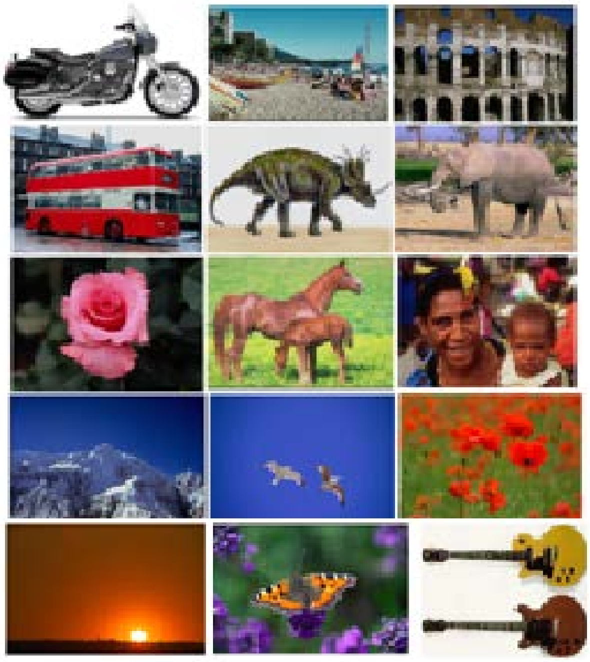

Fig. 4 Sample images from database

The average recall is also calculated in the same manner. The average precision and average recall of this CBIR technique act as an important parameter to find out performance. To determine which method and which color space have better performance.

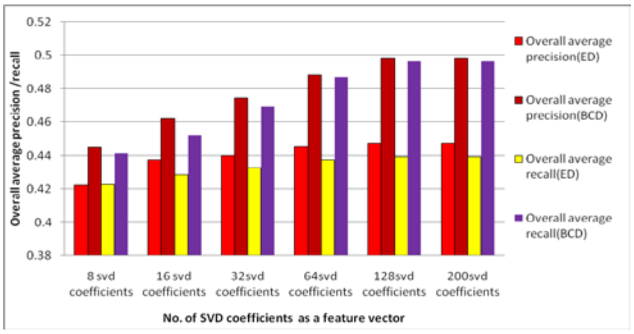

Fig. 5 Overall average precision and overall average recall grayscale image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

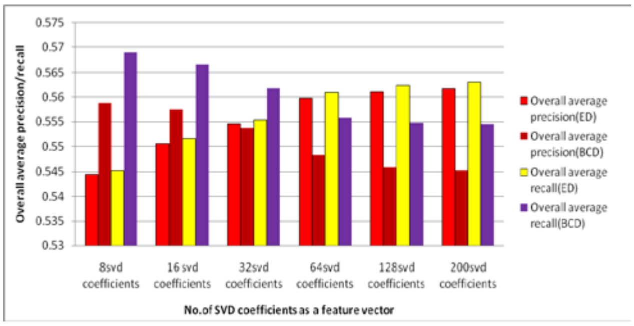

Fig. 6 Overall average precision and overall average recall RGB color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

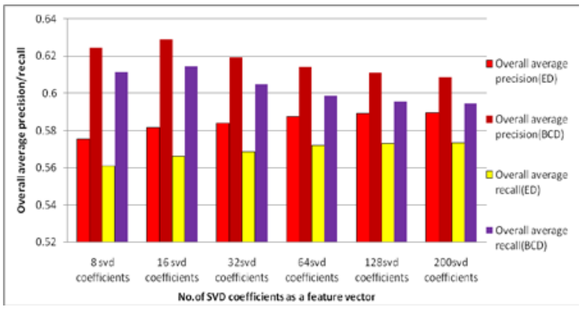

Fig. 7 Overall average precision and overall average recall R'G'I color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

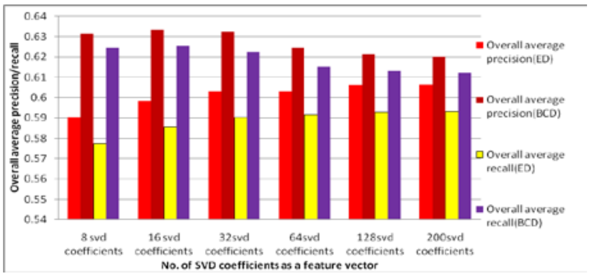

Fig. 8 Overall average precision and overall average recall YCbCr color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

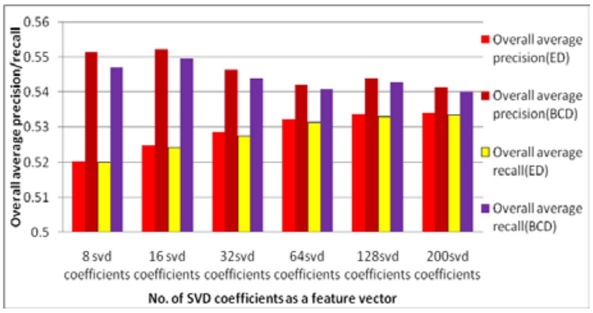

Fig. 9 Overall average precision and overall average recall YUV color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

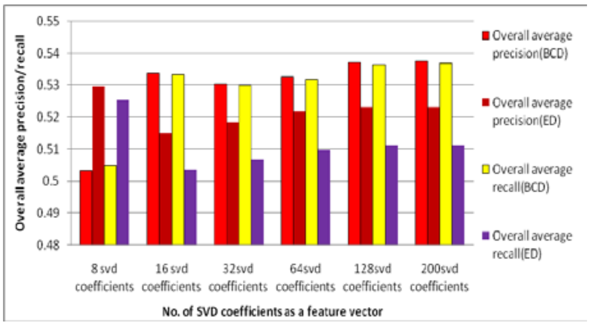

Fig. 10 Overall average precision and overall average recall CXY color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

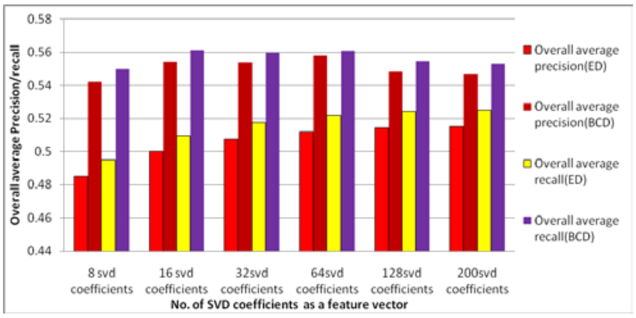

Fig. 11 Overall average precision and overall average recall HSV color image 8,16,32,64,128 and 200 SVD coefficients as a feature vector

Figs. 5-11 shows the Overall average precision and overall average recall cross over point performance for 8 SVD, 16SVD, 32SVD, 64SVD, 128SVD and 200 SVD coefficients of full image SVD respectively for gray scale image, RGB, R'G'I, YCbCr, YUV, CXY and HSV color image. To compare the performance in terms of number of SVD coefficients we compare overall average precision and recall value as listed in Table II and Table III for Euclidean Distance (ED) similarity measure. Table II shows overall average precision values for individual color planes with different SVD coefficients and Table III overall average recall values for individual color planes using Euclidean distance similarity. Overall average precision and recall using Bray Curtis similarity listed in the Table IV and Table V for individual color planes.

TABLE II COMPARISON OF OVERALL AVERAGE PRECISION USING ED OF DIFFERENT COLOR PLANE SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	**No. of SVD Coefficients Used as a Feature Vector**					
	8	**16**	**32**	**64**	**128**	**200**
Gray	0.4222	0.4371	0.4398	0.445	0.446	0.446
RGB	0.5443	0.55052	0.55456	0.5598	0.561	0.5617
R'G'I	0.5753	0.58162	0.58396	0.5875	0.5890	0.5893
YCbCr	0.5902	0.5985	0.6032	0.6032	0.6063	0.6064
YUV	0.5201	0.52473	0.52859	0.5322	0.5336	0.5342
CXY	0.5031	0.53369	0.53027	0.5326	0.5369	0.5374
HSV	0.4850	0.5001	0.50756	0.5120	0.514	0.5151

TABLE III COMPARISON OF OVERALL AVERAGE RECALL USING ED OF DIFFERENT COLOR PLANE SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	**No. of SVD Coefficients Used as a Feature Vector**					
	8	**16**	**32**	**64**	**128**	**200**
Gray	0.4228	0.42844	0.43229	0.4372	0.4392	0.4393
RGB	0.5451	0.55157	0.55533	0.5609	0.5623	0.5630
R'G'I	0.5610	0.56602	0.56856	0.5717	0.5732	0.5734
YCbCr	0.5772	0.58565	0.59003	0.5915	0.5929	0.5931
YUV	0.5199	0.52414	0.52736	0.5314	0.5329	0.5335
CXY	0.5297	0.51513	0.51855	0.5218	0.5230	0.5232
HSV	0.4948	0.50957	0.51742	0.5219	0.5241	0.5251

TABLE IV COMPARISON OF OVERALL AVERAGE PRECISION USING BCD OF DIFFERENT COLOR PLANE SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	**No. of SVD Coefficients Used as a Feature Vector**					
	8	**16**	**32**	**64**	**128**	**200**
Gray	0.4447	0.46198	0.47423	0.4882	0.4983	0.4981
RGB	0.5587	0.55754	0.55368	0.5482	0.5459	0.5452
R'G'I	0.6246	0.62882	0.61945	0.6144	0.6109	0.6088
YCbCr	0.6317	0.63351	0.63261	0.6246	0.6214	0.6201
YUV	0.5513	0.55207	0.54630	0.5419	0.5439	0.5414
CXY	0.5031	0.53369	0.53027	0.5326	0.5369	0.5374
HSV	0.5610	0.61657	0.67873	0.6688	0.5953	0.5464

TABLE V COMPARISON OF OVERALL AVERAGE RECALL USING BCD OF DIFFERENT COLOR PLANE SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	No. of SVD Coefficients Used as a Feature Vector					
	8	*16*	*32*	*64*	*128*	*200*
Gray	0.4414	0.45235	0.46957	0.4871	0.4965	0.4964
RGB	0.5689	0.56660	0.56184	0.5558	0.5547	0.5545
R'G'I	0.6112	0.61460	0.60473	0.5987	0.5957	0.5943
YCbCr	0.6247	0.62544	0.62266	0.6152	0.6132	0.6123
YUV	0.5468	0.54945	0.54394	0.5407	0.5427	0.5400
CXY	0.5047	0.53312	0.52977	0.5317	0.5363	0.5367
HSV	0.5498	0.56137	0.55964	0.5611	0.5544	0.5531

Using Euclidean Distance similarity overall average precision and overall average recall values goes on increasing as SVD coefficients goes on increasing. But in the case of Bray Curtis Distance similarity measure it is opposite, i.e, using 8, 16 and 32 SVD coefficients as a feature overall average precision and overall average recall value is higher and it is goes on decreasing as SVD coefficients increases. YCbCr color image performance is good for both the similarity measures. As can be seen from the above Tables II, III, IV and V, Bray Curtis Distance similarity performs better than the Euclidean Distance similarity.

Figs. 12-18 shows the overall average precision and overall average recall plots of gray scale image, RGB, R'G'I, YCbCr, YUV,CXY and HSV color images respectively with full image SVD, 8X8, 16X16, 32X32,64X64 and 128X128 sub block image SVD coefficients as a feature vector. Overall average precision and overall average recall using Euclidean Distance similarity listed in Tables VI and VII respectively with individual color planes and sub block size. Overall average precision and recall using Bray Curtis similarity listed in the Tables VIII and IX for individual color planes. According to the retrieval result when sub block size goes on decreasing performances also decreases. In Euclidean Distance similarity R'G'I color plane performance slightly greater than the YCbCr color plane. Even for full mage SVD coefficients performance is less than the 128x128 sub block. In this proposed approach also Bray Curtis Distance performance is better than the Euclidean Distance similarity. Retrieval performance of 64x64 sub block SVD of YCbCR color plane is good when compared to the other color planes and other sub bock methods.

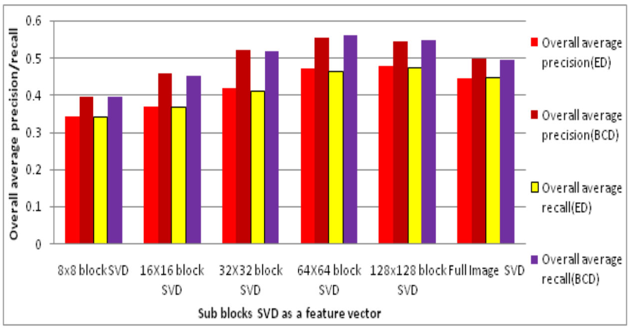

Fig. 12 Overall average Precision and overall average recall for sub block SVD of gray scale image

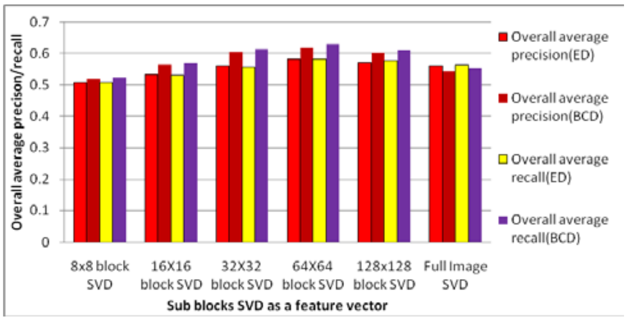

Fig. 13 Overall average precision and overall average recall for sub block SVD of RGB color image

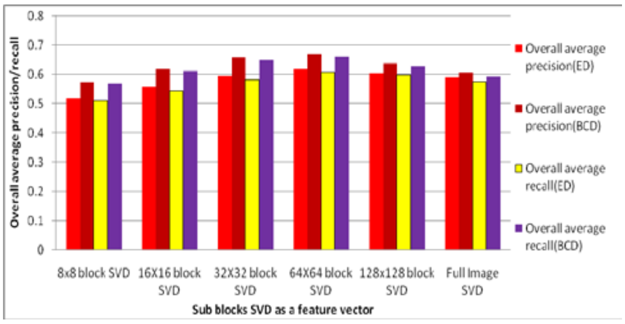

Fig. 14 Overall average precision and overall average recall for sub block SVD of R'G'I color image

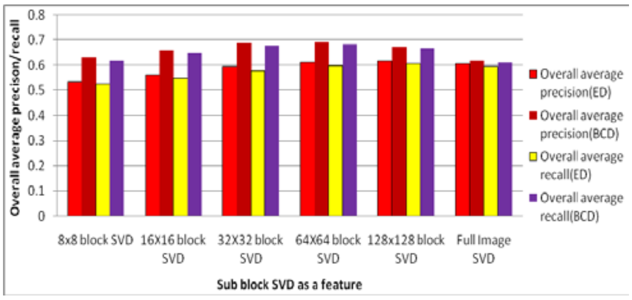

Fig. 15 Overall average precision and overall average recall for sub block SVD of YCbCr color image

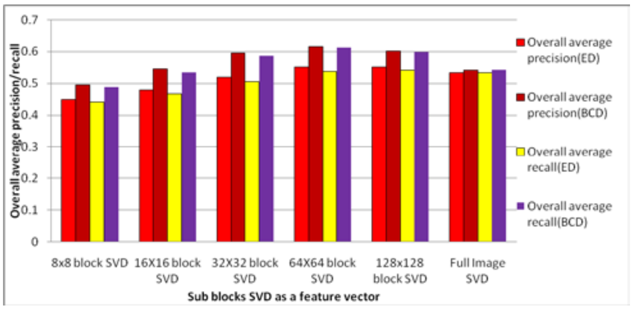

Fig. 16 Overall average precision and overall average recall for sub block SVD of YUV color image

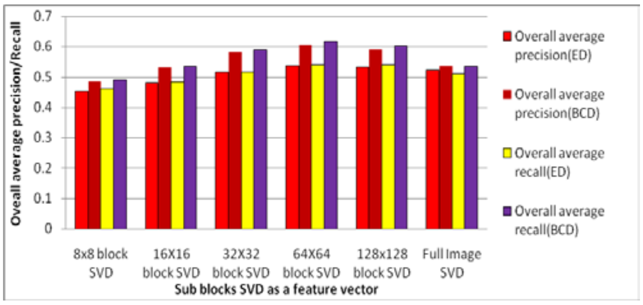

Fig. 17 Overall average precision and overall average recall for sub block SVD of CXY color image

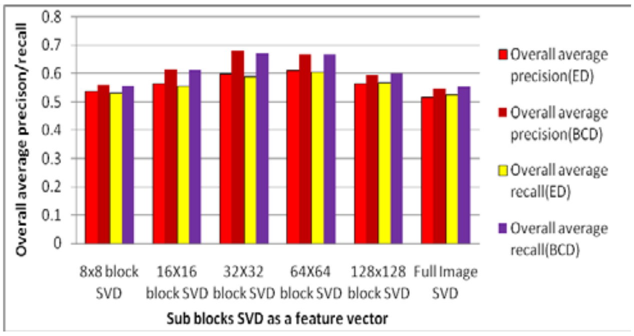

Fig. 18 Overall average precision and overall average recall for subblock SVD of HSV color image

TABLE VI COMPARISON OF OVERALL AVERAGE PRECISION USING ED OF DIFFERENT COLOR PLANE SUB BLOCK SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	Sub Block SVD as a Feature Vector					
	8x8	16x16	32x32	64x64	128x128	256x256
Gray	0.341	0.369	0.4166	0.4698	0.4782	0.44290
RGB	0.507	0.532	0.5598	0.5817	0.57105	0.56175
R'G'I	0.519	0.556	0.5962	0.6185	0.60522	0.58936
YCbCr	0.534	0.560	0.5938	0.6109	0.61639	0.60648
YUV	0.449	0.479	0.52	0.5520	0.55099	0.53421
CXY	0.455	0.481	0.5154	0.5384	0.53298	0.52324
HSV	0.536	0.563	0.5980	0.6111	0.56396	0.51513

TABLE VII COMPARISON OF OVERALL AVERAGE RECALL USING ED OF DIFFERENT COLOR PLANE SUB BLOCK SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	Sub Block SVD as a Feature Vector					
	8x8	16x16	32x32	64x64	128x128	256x256
Gray	0.3430	0.366	0.4109	0.4644	0.47532	0.446403
RGB	0.5075	0.529	0.5573	0.5828	0.57655	0.563012
R'G'I	0.5088	0.542	0.5821	0.6078	0.59725	0.573471
YCbCr	0.5240	0.546	0.5782	0.5977	0.60690	0.593107
YUV	0.4417	0.466	0.5052	0.5381	0.54133	0.533519
CXY	0.4612	0.483	0.5162	0.5402	0.5407	0.5114
HSV	0.5297	0.556	0.5879	0.6028	0.5659	0.5251

TABLE VIII COMPARISON OF OVERALL AVERAGE PRECISION USING BCD OF DIFFERENT COLOR PLANE SUB BLOCK SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	Sub Block SVD as a Feature Vector					
	8x8	16x16	32x32	64x64	128x128	256x256
Gray	0.3952	0.456	0.5205	0.5550	0.54263	0.497297
RGB	0.5187	0.565	0.6054	0.6182	0.60210	0.545263
R'G'I	0.5742	0.618	0.6589	0.6700	0.63927	0.607568
YCbCr	0.6327	0.661	0.6890	0.6927	0.67189	0.619279
YUV	0.4958	0.545	0.5954	0.6160	0.60216	0.542523
CXY	0.5031	0.533	0.5302	0.5326	0.5369	0.5374
HSV	0.5610	0.616	0.6787	0.6688	0.59531	0.546486

TABLE IX COMPARISON OF OVERALL AVERAGE RECALL USING BCD OF DIFFERENT COLOR PLANE SUB BLOCK SVD COEFFICIENTS AS A FEATURE VECTOR.

Image	Sub Block SVD as a Feature Vector					
	8x8	16x16	32x32	64x64	128x128	256x256
Gray	0.3953	0.451	0.5168	0.5598	0.54772	0.495542
RGB	0.3953	0.451	0.5168	0.5598	0.54772	0.495542
R'G'I	0.5682	0.611	0.6497	0.6629	0.62969	0.593186
YCbCr	0.6204	0.649	0.6784	0.6850	0.66556	0.611513
YUV	0.4878	0.533	0.5865	0.6120	0.59899	0.541003
CXY	0.4908	0.535	0.5896	0.6182	0.60246	0.536234
HSV	0.5574	0.610	0.6717	0.6664	0.60075	0.552951

VI. CONCLUSION

The paper has presented a new simple and efficient image retrieval approach using SVD of full image and sub block image. Two similarity measures and seven color planes are used to evaluate the performance of proposed approach. Feature vector is considered as a singular values of each color plane SVD and singular values of sub blocks of each color plane SVD. Luminance color plane performance is for 64x64 sub block SVD is higher than the other color and sub block methods. YCbCr outperform RGB color image by 0.0835 in precision 0.1252 in recall for sub block SVD and YCbCr outperform RGB color image by 0.0759 in precision 0.058 in recall for 16 SVD coefficients of full image considered Bray Curtis Distance similarity. Bray Curtis Distance similarity outperform Euclidean Distance similarity. Block based SVD performance is better than the full image SVD and truncated SVD.

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